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Technical Report 53

DETECTING TOPOGRAPHICAL REGIONS IN DIGITAL TERRAIN MAPS

by

**SABRINA SESTITO
SIMON GOSS
TERRY CAELLI**

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SUMMARY

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This report describes an application of Clustering and Differential Geometry to the characterization of digital terrain maps by different surface types and critical regions. Of particular interest is the determination of specific terrain types, where they occur, and describing them in ways which are invariant to viewing position. The development of robust and efficient segmentation and associated region characterization procedures is reported. Good results have been obtained for characterizing digital terrain maps. This work supports the development of techniques for generating optimal flight paths.

This material was presented as a poster paper at the 5th Australian Joint Conference on Artificial Intelligence, AI'92, Hobart, Tasmania, 1992



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1 INTRODUCTION

Digital terrain elevation map data are comprised of elevation (range) data for a rectilinear grid. Each grid element comprises one arc second of longitude and latitude on the Earth's surface. Methods for mission planning using these data are computationally intensive. If terrain maps can be categorised into higher-level features, such as hills, valleys and planar regions, then the search for an optimal trajectory through the terrain would be greatly reduced. It was felt that the interpretive techniques of machine vision should be applicable to digital terrain maps as they are essentially pixel image data, where elevation is equivalent to a grey scale or range information.

This document describes the results of an investigation of the utility of Computational Vision techniques for the characterization of digital terrain information, the automatic reduction of terrain maps to (multi-scaled) region types and relational, or topographical, graphs. The specific objective was the automatic description of regions in terms of what and where they are in terms which are *invariant* to viewing position. The correct labelling of these regions is critical for optimal flight planning for military operations.

The work described here falls into two areas:

- the investigation of robust and efficient segmentation and region labelling procedures, and
- region feature extraction and generation of symbolic descriptions in terms of relational graphs.

Over the past decade several techniques have been developed for the segmentation and labelling of surfaces for 3D object recognition. These techniques are based upon Differential Geometry [1,2], Clustering [2] and the integration and extension of current Evidence-Based approaches to surface and object recognition [3,4]. These techniques include a detailed set of surface feature extractors, range segmenters, rule generation procedures and matching algorithms.

Many of these techniques have been implemented as part of the Image and Pattern Recognition Scheme (IPRS). IPRS is a library of signal processing, image processing, pattern analysis, pattern recognition and object recognition functions. IPRS can be broken down into functional areas that overlap to some degree. The system is documented in [5]. It currently comprises:

- FM - File and memory routines: saving and loading images, allocating and freeing memory,
- IP - Image processing: including format conversions, filtering, feature extraction, compression and other *early* vision processes,
- CL - Data clustering techniques: standard and new clustering procedures relevant to pattern recognition and rule generation, and

- OPR - Object and Pattern Recognition procedures: techniques developed for the recognition of structures invariant to their rigid motions.

In the interpretation of a map by a mission planner, significant features of navigational importance are identified before the process of logistic constraint-based planning. The identification of features in the map corresponds to the labelling problem in machine vision. This report describes the adaptation of various computer vision techniques to the specific problem of labelling regions of digital terrain range data which correspond to important topographical features for trajectory generation.

2 REGION LABELLING

Terrain data give the elevation of a point on a grid, with respect to mean sea level, usually in a longitudinal and latitudinal format. Thus, elevation data are essentially the complement of range data in the terminology of machine vision and object recognition. For navigation purposes, the data are view-dependent insofar as the depth information is determined as a function of the sensor position. Altitude above the terrain is a function of where you are in the terrain grid and how far above it you are flying.

This type of surface representation is called a Monge patch where depth(z) is a function of the projection plane coordinates (x,y) :

$$z = f(x, y).$$

For flight path planning, it is most important to have a representation for the shape of region parts which is invariant to view direction - given that the region is visible. Fortunately, the surface Mean(H) and Gaussian(K) curvatures have such characteristics, as has been well known for over a century. Not only are they invariant to parameterizations of a surface (in this case, viewer position), but they are also invariant to rigid motions of the surface itself [6]. However, there are several methods of calculating these curvatures and some are more reliable and representative than others [1].

The general strategy used to estimate curvatures involves fitting a surface to a neighbourhood or window centred about each pixel, determining the first and second order partial derivatives of the surface and then using these derivatives in equations for the Mean (H) and Gaussian (K) curvatures [7]. We have used the quadratic surface fitting procedure, which is the most common one used in the literature and which has the advantage of ease of computation of H and K for every NxN window [1]. This procedure is described in Appendix A.

Table 1 shows the eight different region types determined as a function of the signs of the H and K shape descriptors. The region type label is assigned to the pixel in the middle of the window.

	$K>0$	$K=0$	$K<0$
$H<0$	peak	ridge	saddle
$H=0$	(none)	flat	minimal surface
$H>0$	pit	valley	saddle valley

Table 1: Eight Fundamental Surface Types from Curvature Signs

3 SEGMENTATION

Segmentation is a form of clustering where pixels are grouped together in ways which reflect the inherent structures of the data. The determination of such structures can often depend upon the application. In map interpretation this involves determining whether a pixel is part of a feature of interest such as a valley or hill. For instance, consider Figure 1 which shows part of a terrain map. It is fairly obvious to a human observer that the middle section is a valley, where the darker pixels represent lower elevation. In this case, the aim of segmentation is to assign each pixel within a group to a label representing a valley.

The issue of segmentation for range data interpretation has received a good deal of attention in recent years [1,2]. Common to most approaches is the development of surface part clustering in terms of similarities in surface point position normals (ie (x,y,z) coordinates), curvature information or surface curve fitting parameters. Segmentation, in these low-level terms, does not guarantee the derivation of *parts* which are consistent with, for example, *topographical regions* defined by other processes. There have been some attempts to split and merge such initially segmented regions to be consistent with known patch boundary feature bounds; for example, object parts in the database [4]. The nature of our problem led us to explore different segmentation techniques which vary as a function of the degree to which position(*where*) and/or shape(*what*) information is used.

For navigational purposes, the eight features extracted from the H and Ks are too fine. All the pilot requires are the following three general features:

- planar,
- valleys and
- ridges.

The eight fundamental features found in Table 1 were grouped to reflect these broad features; see Table 2.

	K>0	K=0	K<0
H<0	ridge	ridge	planar
H=0	(none)	planar	planar
H>0	valley	valley	valley

Table 2: Three Broad Features relevant to Navigational Purposes determined from the Curvature Signs

3.1 Segmentation by Shape

Segmentation on shape-alone (*what*), ie calculating the H and K values for every window, does not produce realistic or useful *parts* for this type of problem. This is partly because shape does not consider distance information, per se. Also, the data, being so variable, require significant smoothing before computations of curvatures - which, in turn, transform the original data into a terrain envelope. Figure 1 shows the unprocessed terrain map which is used for testing. Figure 2 shows the results of labelling the regions according to the mean and Gaussian curvatures listed in Table 1 for window sizes 3, 5 and 13. Figure 3, on the other hand, present the results when labelling the image according to Table 2, which contain more useful regions for the task of labelling features in digital terrain maps. However, neither result is satisfactory. Segmentation on shape-alone is not sufficient for this problem. The similarity calculated simply in terms of curvature values does not guarantee the necessary contiguity in positional information to obtain reliable labelling of features.

3.2 Segmentation by Position

For segmentation based on position-alone, a segmentation procedure based on clustering was explored (see acknowledgements). In particular, agglomeration was used where each surface point is defined by $(x,y,\alpha z)$ coordinates, where α corresponds to a range sensitivity factor. Agglomeration groups sample points according their distances in feature space, in this case, their scaled coordinates [8,9]. Again, the technique is recursive in so far as points are joined in terms of their relative distances: the data set being ultimately reduced to one point in the following way. First, the nearest two points are fused into one centroid, from this new reduced data set, the process is repeated - until there is exactly one point remaining. The associated tree defines clusters at different levels. From a large number of runs it was empirically determined that the most useful value for α was about 20. However, a major concern with agglomeration is that it computationally expensive and therefore is not a viable solution for large terrain maps.

3.3 Segmentation by Position Using Slicing

In order to improve the labelling of images and to place a greater emphasis on height, the terrain map can be sliced according to elevation. This makes sense according to the physical interpretation of the terrain in the context of aircraft navigation. Here, the map is sliced according to height by determining, for example, equally sized intervals spanning the whole range. Each slice or interval reflects the amount of terrain within a particular interval of height. The slicing intervals can be adapted to fit the range resolution required. Each contiguous area within each slice is treated as a separate entity. Subsequently, when these slices are re-combined into a single map, discrete contiguous areas remain separate.

The steps used for combining the calculation of H and K and slicing are:

- calculate the H and K values for each $N \times N$ window in the image and assign them to the mid-point of the window,
- slice the terrain map into X slices,
- uniquely label the contiguous regions within each slice,
- recombine slices into one map retaining unique region labels,
- calculate the average H and K values for each uniquely labelled contiguous area, and
- assign the map features to unique areas.

Though the solution presented here is not optimized, we have found that equal slices of height produce results which are consistent with the regions perceived to be present in the data. This method has also the advantage of having the ability to control the number of regions via the slice resolution. However, instead of equal slices of depth, slices could be determined using some heuristic based on the physical interpretation of the data.

Figure 4 shows results of slicing the map into 3 slices. Figure 5 shows the resulting recombined map where each uniquely labelled contiguous area is coloured differently. Finally, Figure 6 shows the map labelled according to the labels found in Table 2 and determined from the average curvature values within each region for a window size of 3, 5 and 13, respectively.

The slicing procedure gave similar results to the use of $(x,y,20z)$ in the clustering procedure as described in Section 3.1, where a scaling factor was necessary to emphasise height. The magnification of z demonstrates the importance of the actual range value in the formation of region. However, the computation requirements for determining the slices, labeling each contiguous region within a slice uniquely and then recombining the slices into one map, was found to be minimal compared to agglomeration.

Figure 6 bears the closest resemblance to the original terrain map. With this result, many co-located regions (as shown in Figure 5) are of the same type and after labelling, the unique areas appear to be in the same region (as seen in Figure 6). Overall structures and regions can be clearly identified and located using this combined slicing and feature extraction method.

4 DISCUSSION

At this stage we have shown how one elementary description in terms of connected regions can be obtained from the data. However, further work needs to be done to bring these procedures to completion. In particular, we need to:

- improve the position-only clustering procedures.
- develop range-merging procedures for merging different regions at different heights,
- improve the region labels,
- check the ability of our system to compare labels across views, and
- investigate the types of part features necessary to define regions and their relations.

The next important step to be taken with this work is to develop more advanced symbolic labelling procedures to fit in with the path planning problem. We would like to produce skeleton paths through the various regions. These paths, representing the various regions, could then be used to determine the optimal path through a terrain map. By using these paths, not every pixel within an image needs to be searched or examined, and thus, computational costs will be greatly reduced.

The resulting skeletons representing the various regions could then be used in determining the optimal flight path across the terrain.

One solution to generating these paths involves formulating the problem in state-space [10]. Each state is described by the aircraft's position, orientation and speed, while the cost associated with the state is a function of threat, terrain and the aircraft's manoeuvre required to change the state. The resulting graph can then be searched using A* search. Thus, if the terrain can be categorised into higher-level features, such as hills, valleys and planar regions, then the search space for an optimal trajectory through the terrain would be greatly reduced.

Further work in skeletonisation is required to exploit the techniques in the automatic interpretation of maps in mission planning. That is, to exploit graph search, labelled regions need to be reduced to labelled lines and vertices. This work has commenced.

5 CONCLUSIONS

In this study we have determined the feasibility of producing, from input terrain maps, a symbolic topographical description of the data. A digital terrain map can be regarded as an image made up of pixels. Thus, a number of computer vision techniques can be used to identify terrain features for navigational purposes.

We have found that the most efficient and reliable method involves combining the calculation of the mean (H) and Gaussian (K) curvatures and slicing. Segmenting the map with respect to positional information and then labelling each contiguous region for surface types results in the *what* and *where* topographical map. We have shown that

machine vision techniques have application on data types outside their original conception in object recognition.

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REFERENCES

- [1] Besl, P. & Jain, A., 1986, Invariant surface characteristics of 3D object recognition in range images, *Computer Vision, Graphics and Image Processing*, 33, 33-80
- [2] Hoffman, R. & Jain, A., 1987, Segmentation and classification of range images, *IEEE Pattern Analysis and Machine Intelligence (PAMI)*, 9(5), September, 608-620
- [3] Caelli, T. & Drier, A., 1992, Some new techniques for evidence-based object recognition : EB-ORS1, Proceedings of the 11th IAPR International Conference on Pattern Recognition, The Hague, The Netherlands, 450-454
- [4] Jain, A. & Hoffman, R., 1988, Evidenced-based recognition of 3D objects, *IEEE Pattern Analysis and Machine Intelligence (PAMI)*, 10(6), 783-802
- [5] Dillon, C., 1993, *IPRS: Image Processing and Recognition System. User and programmer's manual*, Department of Computer Science, University of Melbourne
- [6] DoCarmo, M., 1976 . *Differential Geometry of Curves and Surfaces*, New Jersey: Prentice-Hall
- [7] Flynn, P. & Jain, A., 1989, On reliable curvature estimation, Proceedings of *IEEE Conference on Computer Vision and Pattern Recognition*, San Diego
- [8] Hartigan, J. A., 1975, *Clustering Algorithms*, New York:Wiley
- [9] Kurita, T., 1991, An efficient agglomeration clustering algorithm using a heap, *Pattern Recognition*, 24(3), 205-209
- [10] Selvestrel, M. and Goss, S., 1993, Optimal trajectories for aircraft using state space search, Proceedings of the *Artificial Intelligence in Engineering (AIENG-93)* conference, Toulouse, France

Figure 1. Original terrain map (128*128 pixels)



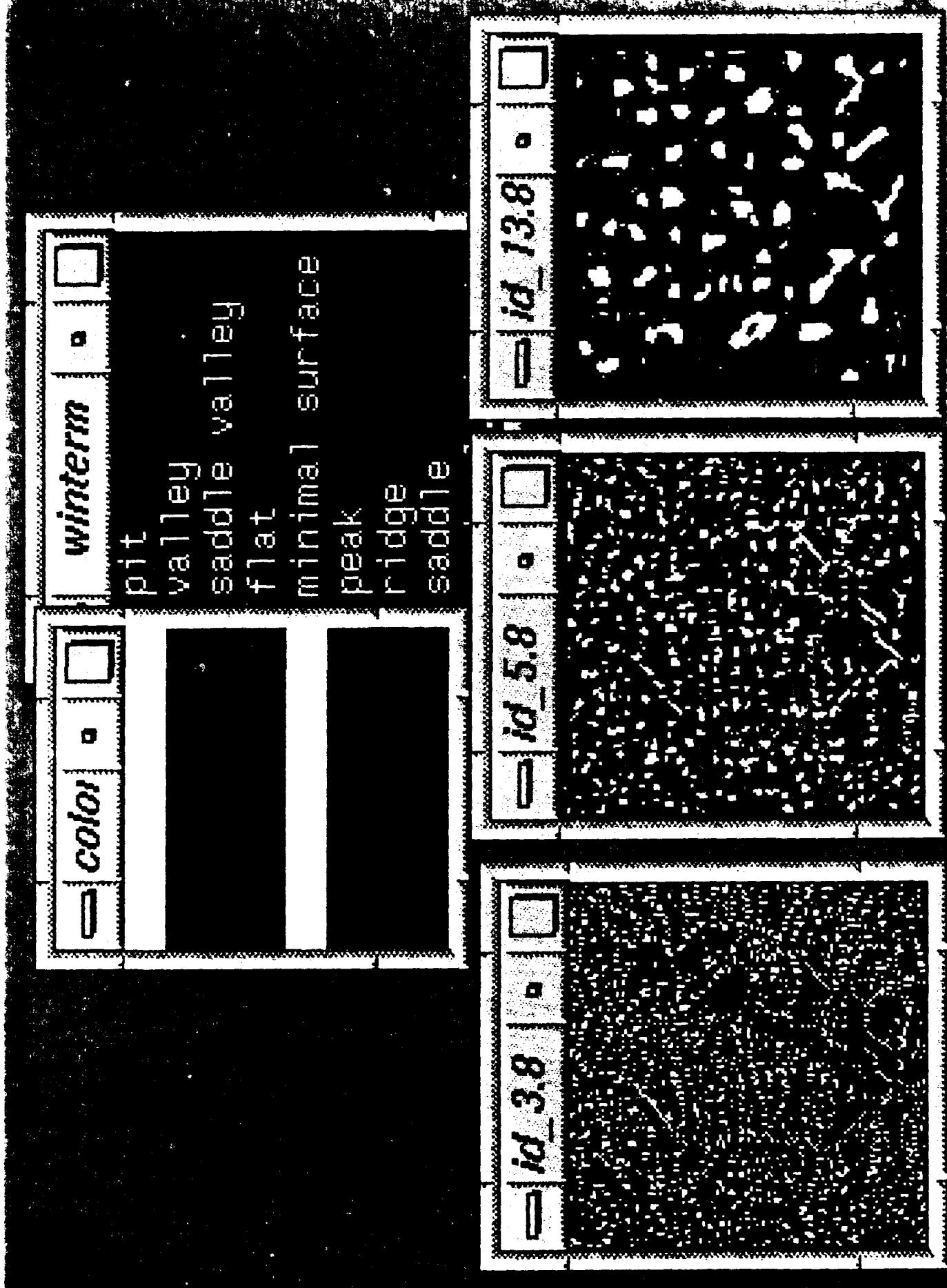


Figure 2. Map labelled according to H and K listed in Table 1, for windows 3,5 & 13, respectively

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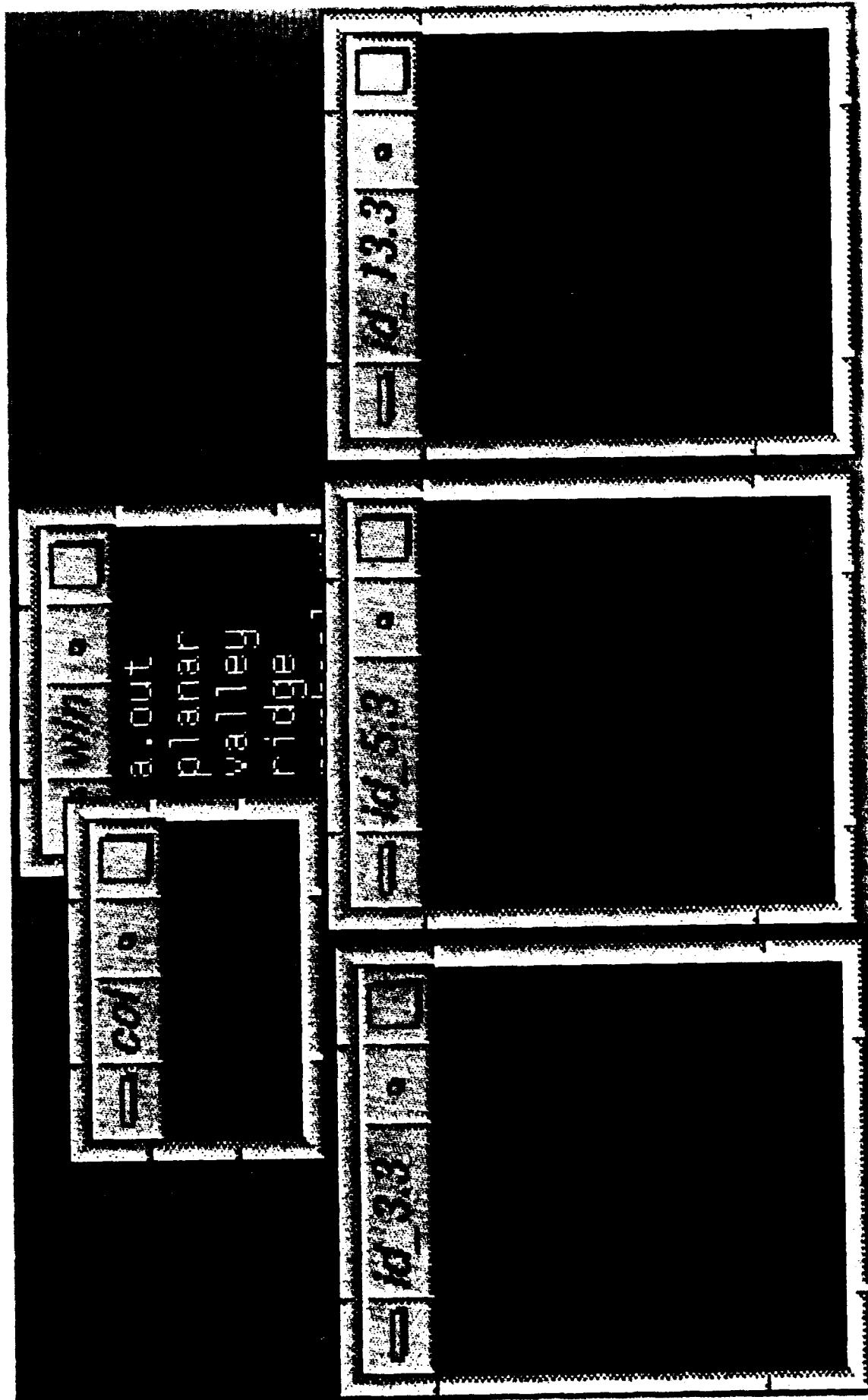


Figure 3. Map labelled according to H and K listed in Table 2, for windows 3.5 & 13, respectively

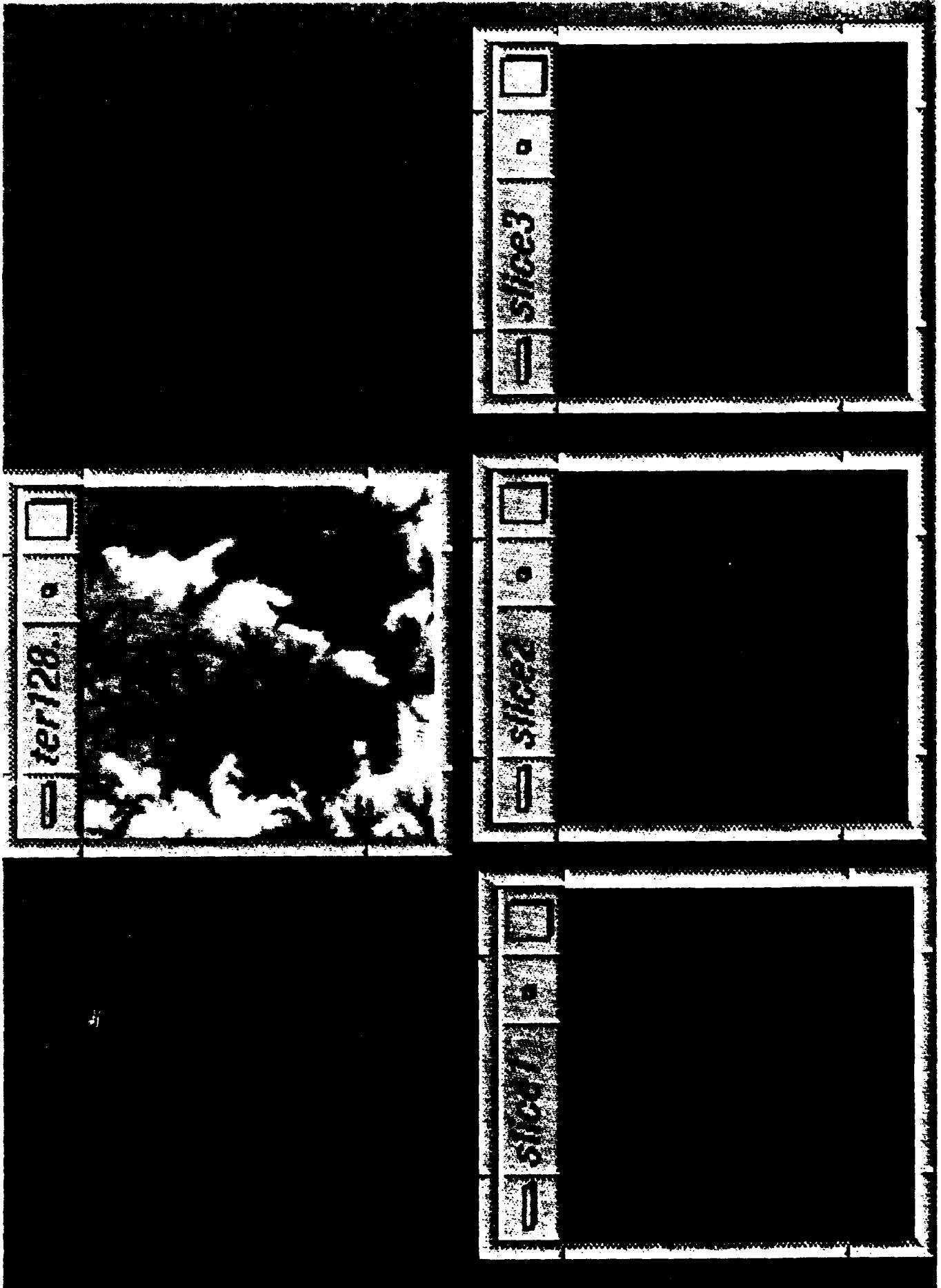
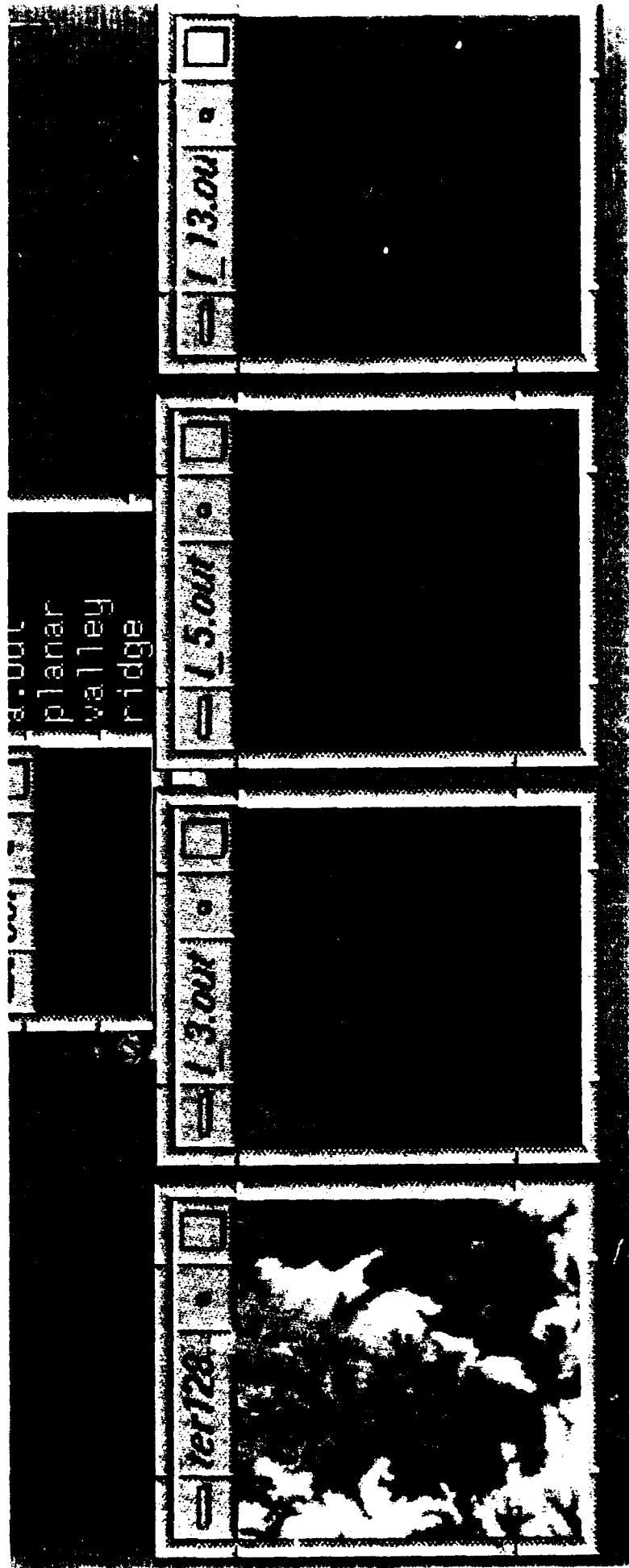


Figure 4. Map sliced into 3 slices



Figure 5. Slices recombined into one map, with contiguous regions labelled uniquely

Figure 6. Labelled recombined map according to average H and K, according to Table 2



APPENDIX A

Calculating the Mean (H) and Gaussian (K) Curvatures

The approach used in this quadratic fitting procedure is the following:

- given discrete sample data, a continuous differentiable function that 'best' fits the data is to be determined, and
- compute the derivatives of the continuous function analytically and then evaluate them at the corresponding discrete points.

Ideally, we would like to fit one smooth surface to all the data. This is not computationally feasible. Instead, a local surface fit is determined for each NxN window in the map. A local quadratic surface model is used for this purpose. Experimental results have shown that this approach is adequate¹.

For a given window size (*scale*) the (least squares) best fitting quadratic surface range value is computed, over an NxN window at position (x,y), as:

$$f'(x,y) = \sum_{ij} a_{ij} \phi_i(x) \phi_j(y)$$

where a_{ij} are selected to minimize the error term:

$$e = \sum_{xy} (f'(x,y) - f(x,y))^2.$$

The following discrete orthogonal polynomials, ϕ s, provide the quadratic surface fit:

$$\phi(u) = 1$$

$$\phi_1(u) = u$$

$$\phi_2(u) = \{ u^2 - (M(M+1)) / 3 \}$$

for $M = (N-1)/2$, ie half the window size. The a_{ij} terms are determined by:

$$a_{ij} = \sum_{xy} f(x,y) b_i(x) b_j(y)$$

¹ Besl, P. & Jain, A., 1986, Invariant surface characteristics of 3D object recognition in range images. *Computer Vision, Graphics and Image Processing*, 33, 33-80

where the b terms are normalized versions of the orthogonal polynomials (1):

$$b_0(u) = 1 / N$$

$$b_1(u) = 3 / (M(M+1)(2M+1)^u)$$

$$b_2(u) = 1 / P(M) \times \{ u^2 - (M(M+1) / 3) \}$$

where

$$P(M) = 8/45 M^5 + 4/9 M^4 + 2/9 M^3 - 1/9 M^2 - 1/15 M.$$

Thus, computing the a terms using odd sized windows is simple, because the bs are precomputed for any window size. From the a terms, the first and second partial derivative estimates are then given by:

$$f_x = a_{10},$$

$$f_y = a_{01}$$

$$f_{xy} = a_{11},$$

$$f_{xx} = 2 a_{20}, \text{ and}$$

$$f_{yy} = 2 a_{02}.$$

The residual squared-error image is determined by:

$$e(x,y) = (f'(x,y) - f(x,y))^2.$$

It is important to note that such smoothing results in errors at discontinuities or region boundaries. However, as we are concerned with broad region categories and their location, this has no significant effect in the computations of surface shape.

The H and K values can then be determined using the following equations:

$$H = \frac{1}{2} * \frac{(f_{xx} + f_{yy} + f_{xx}f_y^2 + f_{yy}f_x^2 - 2f_x f_y f_{xy})}{(1+f_x^2+f_y^2)^{3/2}} \quad \text{and}$$

$$K = \frac{f_{xx} f_{yy} - f_{xy}^2}{(1 + f_x^2 + f_y^2)^2}.$$

These equations apply to a Monge patch (view-dependent depth map) case where f_{uv} refers to partial differentiation of f with respect to u and v and $f(x,y)$ to the view-dependent range image. Such computations are enacted after the initial quadratic surface fitting procedure.

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